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The optimization of conservation agriculture practices requires attention to location-specific performance: Evidence from large scale gridded simulations across South Asia

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A R T I C L E I N F O

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Rice-wheat system
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Gridded crop model
Spatial optimization

A B S T R A C T

The ways in which farmers implement conservation agricultural (CA) practices – which entail reduced tillage, maintenance of soil cover, and crop rotations – varies considerably in different environments, farming systems, and by the intensity with which farmers administer management practices. Such variability requires an efficient tool to evaluate the cost-benefit of CA, to inform agricultural policymakers and development priorities to facilitate expanded use of CA under appropriate circumstances. Rice-wheat rotation is the principal production system in South Asia (SA). Research has shown that CA can be promising in this rotation because of improved irrigated water, energy, and labor use efficiencies, in addition to the reduction in atmospheric pollution and potentially long term improvements in soil quality. Yield responses to CA are however varying across studies and regions. With a nine-year rice-wheat CA experiment in Eastern Gangetic Plains of South Asia, this study parameterizes the Environmental Policy Climate (EPIC) model to simulate five CA and conventional managements on the RW cropping system. Information from geospatial datasets and farm surveys were used to parameterize the model at the regional scale, increasing the management flexibility and range of localities in the simulation. Yield potential of the CAs in the whole SA was thereby explored by utilizing the model with various management strategies. Our results demonstrate how geospatial and survey data, along with calibration by a long-term experiment, can supplement a regional simulation to increase the model's ability to capture yield patterns. Yield gains from CA are widespread but generally low under current management regimes, with varied yield responses among CAs and environments. Conversely, CA has considerable potential in SA to increase rice-wheat productivity by up to 38%. Our results highlight the importance of applying an adaptive definition of CA, depending on environmental circumstances, while also building the capacity of farmers interested in CA to apply optimal management practices appropriate for their environment.

1. Introduction

Agricultural productivity in South Asia (SA) faces significant challenges to match future food demand while using natural resources judiciously (Stevenson et al., 2014). In response, conservation agriculture (CA) has been widely promoted as an alternative to tillage-based

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conventional agriculture and an approach to crop husbandry that can reconcile these often competing objectives (Jat et al., 2020). CA is a management system of agronomic technologies that allow for minimum soil disturbance, maintenance of a permanent soil cover, and spatio-temporal diversification of crop species (Pittelkow et al., 2014). Research suggests that CA has multiple benefits, including the saving of labor, energy, mineral nitrogen in farming and leading to reduction in greenhouse gas emission (Alam et al., 2019), enhanced biological activity in soils (Naresh et al., 2016), and the long-term yield and productivity increase as a consequence (Sharma et al., 2012). In the short term and irrigated environments, some studies have suggested that CA has no yield advantages if not optimally implemented (Pittelkow et al., 2014). The area under CA in SA is also relatively small compared to temperate nations and South America (Somasundaram et al., 2020). The coverage of partial CA-based system (at least one crop with no-till, with or without residue retention) is estimated around 2.5 million ha in South Asia (Jat et al., 2020), equivalent to 1% of total arable land, which remains much lower than the proportion in America, Europe, Australia, and China (Kassam et al., 2018).

CA in SA started with the direct seeding of wheat in Punjab states of India and Pakistan (Hafeez-Ur-Rehman et al., 2015). Many agronomic challenges, including the prevalence of weeds, insect pests, diseases, the lack of widespread and suitable systems for managing crop residues, and the nonavailability of proper seeding and planting equipment, affect the adoption of CA in SA (Jat et al., 2021). Productivity under CA also varies considerably among and across the environments, depending on the crop, location, climate, management, how many and how long the three principles of CA have been applied. Some reviews have shown that no-till practices can reduce crop productivity, but no-till with residue retention and crop rotation may increase yield (Jat et al., 2020; Kumara et al., 2020). While many researchers have generated data across cropping systems in different geographical areas, CA's yield potential has not been examined across various agronomic and environmental factors.

The rainy ('*kharif*') season rice winter season ('*rabi*') wheat (RW) cropping sequence is the most important and widely adopted rotational pattern in SA. It occupies 13.5 million hectares of area, mostly in the Indo-Gangetic Plains (IGP) of India, Bangladesh, Nepal, and Pakistan (Gupta and Seth, 2007). Conventional RW production system is labor, water, capital, and energy-intensive (Bhatt et al., 2016), resulting in over-exploitation of groundwater, soil degradation, and increase in atmospheric pollution (Shyamsundar et al., 2019). Soil with poor physical and biological health does not respond either to higher doses of fertilizers and other agricultural management inputs, nor able to cope with the climate change shock. Along with the weed flora shifts, herbicide resistance in weeds, outbreak of diseases, insect and pests, lower nutrient use efficiency, labor shortage, multinutrient deficiencies are other sustainability issues causing yield stagnation in RW system (Bhatt et al., 2016; Ladha et al., 2003; Timsina and Connor, 2001). To overcome these emerging constraints of yield plateau, increasing cost of labor, water, and energy and declining farm profitability, farmers have been encouraged to explore alternative options for tillage, crop establishment, and management practices (Bhan and Behera, 2014). Various experiments have been conducted to address the optimization of RW systems productivity under CA in SA, with multiple benefits on productivity, profitability, and environmental sustainability (Sharma et al., 2018; Singh et al., 2020; Gathala et al., 2011; Choudhary et al., 2018). However, long-term experimental studies are difficult to reliably implement, in addition being expensive to maintain. Another challenge related to long-term experiments concerns the extrapolation of results to farmer practice (Su et al., 2021). It is impossible to explore all CA practice combinations across the full suite of SA's diverse soil and climates. Furthermore, the difference in yield outcomes and contrasting performance across the treatments may take several years to appear, given the varied, primary drivers, of soil and climate. Economic conditions such as inputs, energy, and labor cost are also dynamic and change by location and with time. Consequently, static treatments compared in a long-term field experiment may become inappropriate for application in practice by farmers by the time reliable results become available (Cabelguenne et al., 1990). In addition, it is increasingly recognized that there is no universal template for CA; rather, farmers' practices require a process of adaptation to local conditions and constraints to optimize system performance in different environments (Kienzler et al., 2012). For example, following rice harvest, the planting window in the rice-wheat system and the duration of winter season is relatively shorter in the Eastern IGP than Western IGP. So, the yield penalty due to delayed planting is higher in the east than in the west with the same practice (Jat et al., 2020). Given this difference and wide diversity in agroecological conditions across SA, testing and refinement of CA-based cropping practices are required for its widespread adaption. This however is logistically impossible with most long-term experiments.

Mathematical models that simulate biophysical processes are one means of evaluating complex agricultural systems, such as the RW system in SA (Timsina and Humphreys, 2006). When applied on a gridded spatio-temporal basis, simulation models can offer a quicker and less expensive way of investigating the effects of agricultural management practices on crop growth across environments. With reliable observed field data and precise calibration methods, models have been applied to design management strategies (Shahid et al., 2020), test the effectiveness of management practices (Assefa et al., 2020), and examine the environmental and social consequences (e.g. economic, labor demand, household labor availability) of a production system (Daloglu et al., 2014). Many models have been improved to simulate crop sequences, such as the RW rotation (Kollas et al., 2015; Timsina et al., 1998), and some have been used to investigate the impacts of CA (Corbeels et al., 2016). However, there are relatively few cases in SA where crop models have been applied to simulate and explore management options for CA across a spatio-temporal gradient of agroecological conditions. This is likely attributed to the scarcity of relevant data on diverse management practices of CA, the complexity of environments encountered in SA, and individual model limitations, such as the requirements of large inputs and detailed calibration.

This study aims to (1) integrate a long-term CA experiment, farm survey, and geospatial data to set up a gridded crop model to examine the effect of CA on RW system productivity in SA, (2) apply the model with five CA strategies with different levels of agronomic interventions under the RW system, and (3) to optimize management practices for higher crop productivity across diverse environments.

2. Materials and methods

As most of the RW cropping system is concentrated in the Indo-Gangetic Plains (IGP) spanning India, Pakistan, Nepal, and Bangladesh, we set up the simulations across these countries (Fig. 1). The simulations were conducted at a 25 km $\times$ 25 km grid scale for all rice or wheat grids, with daily weather inputs (1981–2019), soil and managemental information. First, we set up the RW rotation in the model at a regional scale with gridded geospatial data, including weather, soil, topography, fertilizer, and crop calendar. These gridded datasets have been used by multiple Global Gridded Crop Models (GGCMs, e.g. Muller et al., 2017). Second, to improve the model performance on CA, we calibrated model's tillage parameters, with observations from a 9-year CA experiment in India. Third, by using a model optimization algorithm and operation information relevant to the CA practices in local of CA trials and farm surveys, we optimized model managemental parameters in each grid to accommodate the location-specific characteristics in crop cultivars and corresponding rotation settings. Last, we estimated the yield potentials of the RW system for each CA, under different nutrient strategies. These steps and data sources are described in Fig. 2 and below.

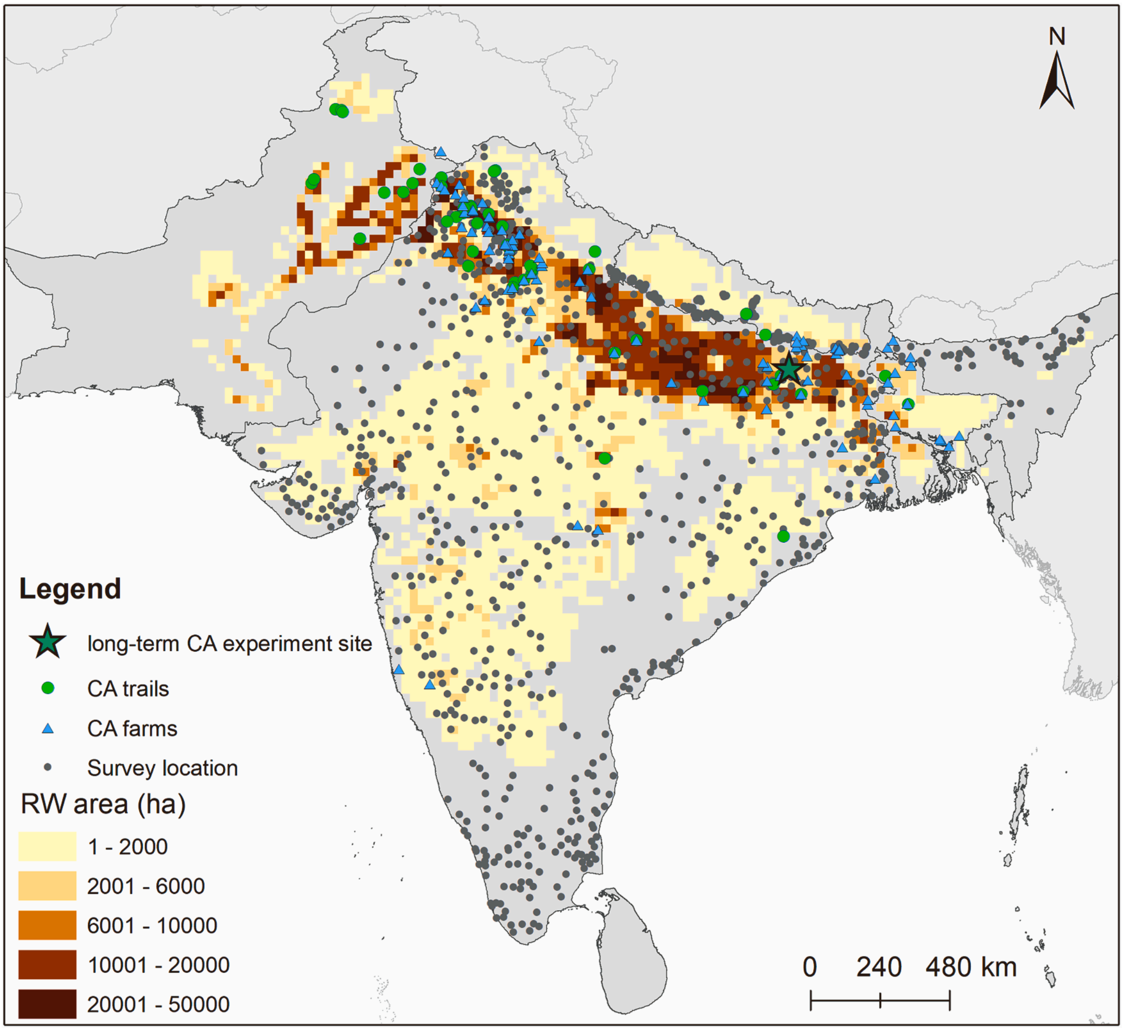

Fig. 1. Simulation domain, the long-term CA experiment site (Jat et al., 2014), the CA trial and farm sites collected in the meta-analysis study (Jat et al., 2020), and farm survey villages.

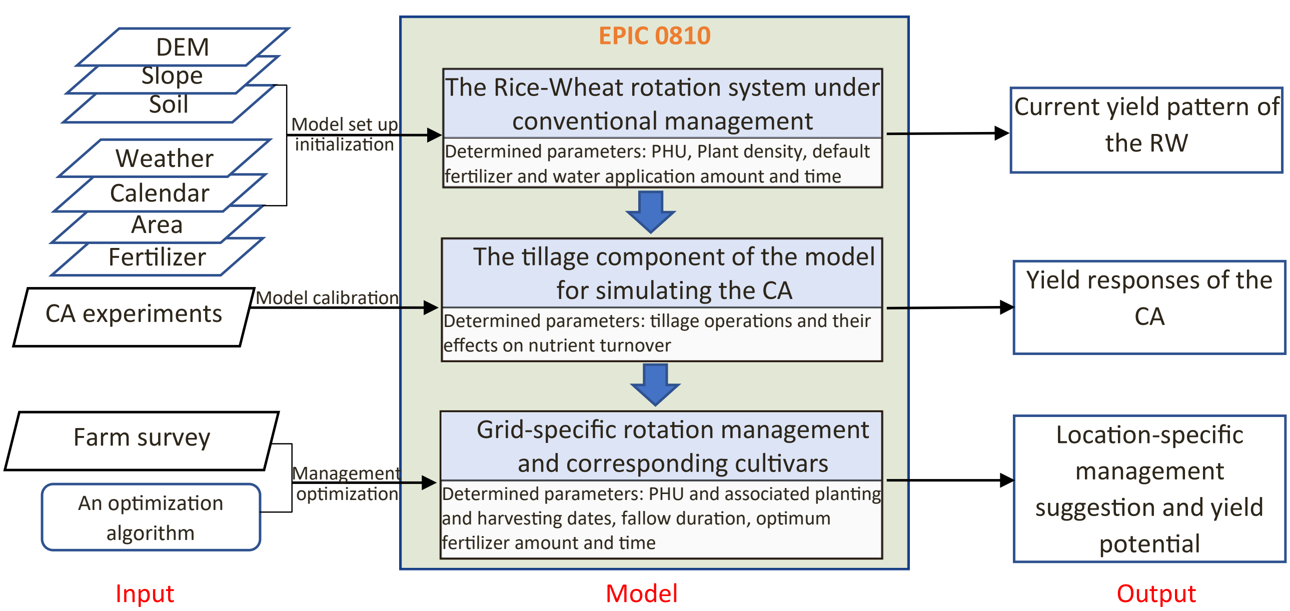

Fig. 2. Flow chart of the EPIC simulation for CA.

2.1. The EPIC model

The Environmental Policy Integrated Climate (EPIC) model (version 0810) was originally developed to simulate interactions between soil, climate, and management practices and their effects on soil erosion and the long-term consequences of soil quality decline on productivity and nutrient requirements. The main modules include weather generation, crop growth, soil water dynamics and temperature, soil erosion, carbon and nutrient cycling (Xiong et al., 2016; Balkovic et al., 2014). The crop growth module simulates light interception, radiation conversion to biomass, partitioning to roots, shoots and economic yield, and water and nutrient uptake. Plant growth is constrained by water, nutrient, air temperature, and soil aeration stresses.

We chose this model because it can simulate the effects of a variety of agricultural practices on crops (e.g. wheat, rice, maize), including various tillage methods (Le et al., 2018). EPIC can also simulate multiple crops grown in complex rotations and has been used to examine the effects of conservation tillage practices, interactions between tillage and residue management, irrigation, liming, and application of fertilizer N and P (Le, 2017; Le et al., 2018). The model's economics module uses a crop budget to calculate production costs. Income is determined from input market prices and simulated annual yield for crops and forages. The EPIC tillage module was conversely designed to simulate the mixing of nutrients and crop residues within the plow depth that affects bulk density, and to represent the conversion of standing stubbles into flattened residues. Within the modeling environment, tillage operations affect ridge height, surface roughness, bulk density and also mix soil layers, nutrients, and plant residues.

2.2. Data

Geospatial data used to set up the baseline simulation included weather, topography, soil, crop management, land cover, and plant parameters. Most datasets came from public sources and were stored at the simulation grid scale.

2.2.1. Climatic data

Gridded daily weather variables (including maximum and minimum temperatures, incoming shortwave radiation, rainfall, vapor pressure deficit, relative humidity, and wind speed) were obtained from the newest weather product (AgERA5) generated by ECMWF (European Centre for Medium-Range Weather Forecasts) for 1981–2019. AgERA5 is based on hourly ECMWF ERA5 data at sea level. ERA5 is a global reanalysis provided at ~30 km resolution, with consistent data sequences from 1979 onwards at hourly and monthly intervals. AgERA5 is generated by downscaling ERA5 at 9 km resolution using a nearest neighbor interpolation and correcting biases employing a linear approach (ECMWF, 2020).

2.2.2. Topographic data

Topographic data were obtained from the global 30 arc-second digital elevation model (DEM) (GTOPO30), a 1 km resolution dataset made available by the United States Geological Survey (USGS EROS Data Center). The high-resolution global Shuttle Radar Topography Mission DEM from NASA (Farr et al., 2007), which uses a 3′ spatial resolution, was used as a source for calculating slope.

2.2.3. Soil data

Soil parameters (soil texture, bulk density, pH, organic carbon content, and the fraction of calcium carbonate for each of five 20 cm thick soil layers) were retrieved from the International Soil Profile Dataset (WISE) (Batjes, 1995). Soil parameters were allocated to each simulation grid cell based on the spatially dominant soil type taken from the digital Soil Map of the World (F.A.O., 1990). Soil water retention and hydraulic parameters were calculated using pedo-transfer functions (Schaap and Bouten, 1996). Parameters for organic contents missing in the WISE dataset were adopted from Boogaart et al. (1998). The 5′ spatial resolution model on global cropland use produced by You and Wood (2006) was used as a source of cropland extent data.

2.2.4. Crop coverage data

Crop yields and harvested area were obtained from a gridded dataset by combining two products of Monfreda et al. (2008) and the Spatial Production Allocation Model (SPAM) (You et al., 2009), reflecting production in the year 2000. Cropping calendars were sourced from the Center for Sustainability and Global Environment (SAGE). This dataset is the result of digitizing and geo-referencing existing observations of crop planting and harvesting dates, at a resolution of 5′ (Sacks et al., 2010). The dataset provides approximate planting and harvesting windows for different crops. A 5′ crop-specific gridded dataset representing nitrogen, phosphorus, and potash fertilizer application for the year of 2000 was used in baseline model setup to represent macronutrient application rates. This dataset is based on a spatial disaggregation approach that fuses national and sub-national fertilizer application data from various sources into a unified product (Mueller et al., 2012).

2.2.5. Data on farmers' management practices

Present production characteristics of the RW cropping system in SA were developed based on detailed farm surveys that were conducted in 2019–2020 in India, Bangladesh, and Nepal. The detailed farm surveys consisted of 7378 randomly selected farmers, with information characterizing field locations, sizes, and land allocated to specific crops, production inputs (seeds, irrigation, fertilizer, labor, and fuel/energy use), management practices (nutrient and agrochemical types, rates, and application times, sowing, transplanting and harvesting dates, and the cultivar maturity group / approximate duration of cultivars), the household structure (size and composition of the family), the land use in terms of cropping systems (field size and share for crops), and monetary flows. From this comprehensive dataset, we extracted information on crop establishment dates, use of nutrients and water, as well as crop duration to define the range of management parameters used for crop management optimization.

2.2.6. Data on the performance of conservation agriculture

EPIC has been well-calibrated and tested at both global and regional scales for rice and wheat (Xiong et al., 2014; Wang et al., 2018), but not for crop sequence and CA practices. Therefore, we used a nine-year conservation agriculture experiment in rice-wheat rotation in SA during 2006—2014 to calibrate the tillage component of the model. The calibration was focused on the RW cropping system, particularly the soil nutrient related parameters and the effects caused by tillage. The nine-year CA experiment was conducted in the research farm of Rajendra Agricultural University, Samastipur, Bihar, India (25̊25′51″N, 85̊40′31″E). The long-term trial was established during monsoon 2006 involving various combinations of tillage, crop establishment, and residue management practices in a rice-wheat rotation (Table 1). The soil of the experiment site is clay loam with medium organic matter content (0.68%). The climate of the site is characterized by hot and humid summers and cold winters with an average annual rainfall of 1344 mm, 70% of which is received between July to September. For further details of the trial and its results refer to Jat et al. (2014).

An additional data set from a published meta-analysis study of conservation agriculture in SA (Jat et al., 2020) was used to benchmark our simulation results. The metadata contained 2741 paired comparisons for rice and wheat under conventional and CA practices, with different performance indicators under various CA categories, cropping systems, and soil textures. These paired observations were derived from 155 on-station studies carried out from 2000 to 2018 and a total of 1197 paired data points from 1097 on-farm studies carried out during 2003–2018 across SA (Fig. 1). We categorized the paired data points into the six categories in the Table 1 according to their experimental descriptions. Data that could not be categorized were removed. Finally,

Table 1
Abbreviation and description of tillage, crop establishment and residue management protocols under six treatments that chosen in the study.

S. No.	Treatment abbreviation	Tillage		Crop establishment		Residue management	
		Rice	Wheat	Rice	Wheat	Rice	Wheat
1	CTR-CTW	3 passes of dry tillage with harrow, 2 passes of cultivator in ponded water	2 passes of harrow, 1 pass of cultivator followed by 1 planking	Manually transplanted, random geometry	Broadcasting, random geometry	All removed	All removed
2	CTR-ZTW	Same as CTR-CTW	Zero till	Same as CTR-CTW	Direct drilling on flat soil and row geometry	All removed	All removed
3	ZTDSR-CTW	Zero till	2 passes of harrow, 1 pass of cultivator followed by 1 planking	Direct dry seeding on flat soil, row geometry	Broadcasting, random geometry	All removed	All removed
4	ZTDSR-ZTW	Zero till	Zero till	Direct dry seeding on flat soil, row geometry	Direct drilling on flat soil and row geometry	All removed	All removed
5	ZTDSR-ZTW+R	Zero till	Zero till	Direct dry seeding on flat soil, row geometry	Direct drilling on flat soil and row geometry	50% rice residue retained in wheat cycle	25% wheat residues retained in rice cycle
6	PBDSR-PBW+R	Zero till	Zero till and reshaping of beds	Direct dry seeding on permanent beds	Direct drilling on permanent beds	50% rice residue retained in wheat cycle	25% wheat residues retained in rice cycle

CTR–CTW: conventional till puddled transplanted rice followed by conventional tilled wheat; CTR–ZTW: CTR followed by zero tilled wheat; ZTDSR–CTW: zero-till direct seeded rice followed by CTW; ZTDSR–ZTW: ZTDSR followed by ZTW without residues; ZTDSR–ZTW+ R: ZTDSR followed by ZTW with residues; and PBDSR–PBW+ R: direct seeded rice followed by wheat both on permanent raised beds.

simulated yields under CA and conventional practices were compared at different locations across the IGP.

2.3. Model setup, parameterization, and management optimization

We employed three steps to set up (initialize), calibrate, and optimize the rotation management of the RW system in SA. We first set up the model for rice and wheat separately in SA at the regional scale by using the Global Gridded Crop Models (GGCM) approach. In total, 6073 grid cells with either reported rice or wheat area were selected as the simulation unit by resampling the reported gridded crop area, in which 4662 grids were retained as rice pixels and 3645 grids as wheat cells (Fig. 1). EPIC had been calibrated and validated for rice and wheat at both regional and global scales in prior studies. We adopted the parameterization method that was developed for global scale geospatial data (Xiong et al., 2014; Balkovic et al., 2014; Wang et al., 2018). For example, the middle points of the reported sowing and harvesting window from SAGE were used to compute the Potential Heat Unit (PHU). The potential Harvest Index (HI) and Biomass-Energy Ratio (WA) were adjusted in each grid to decrease the difference between simulated and reported mean crop yields. For this baseline simulation, rice-wheat rotation in all grids with both rice and wheat area was simulated from 1980 to 2019. The first 20 years (1980–1999) was used as the spin-up run to reach an equilibrium of soil carbon and nutrient because of the unavailability of soil initial conditions.

Secondly, we calibrated the model for the RW rotation and CA with the nine-year CA experimental data by adjusting crop, soil, and tillage parameters. Reported yield, biomass, and phenology from the long-term trial were used to calibrate the model, with inputs of the gridded weather and soil data, observed crop calendar, tillage approach, time and amount of fertilizer and chemical application. For this calibration, we first varied model parameters of potential heat units (PHU), radiation conversion to biomass, and harvest index to decrease the difference between observed and reported mean phenology/yield under CTR-CTW over the 9 years. EPIC's option for continuous soil process was chosen during the simulation to represent the long-term effects of rotation. For the CA simulation, we modified four nitrogen and soil relevant parameters to improve the simulation of the long-term Soil Organic Carbon (SOC) and nitrogen dynamic in tropic and semi-tropic soil. Because the long-term experiment lacked SOC and soil nutrient data, this modification was based on prior SOC calibration conducted in Combodia (Le, 2017), where the soil and climate are analogous to that in SA. CAs involve different tillage practices, including crop establishment, plowing, and residue mixing methods. We reflected these differences by defining the sequence and type of each tillage operation from the EPIC default tillage operations database. We also adjusted five tillage parameters in each tillage operation, including plow depth, changes in bulk density, converting ratio of standing residue to flat residues, ridge height, and surface roughness. These parameters potentially affect nutrients and residue use efficiency, resulting in contrasting yield and yearly trend for current and subsequent crops. This adjustment was conducted manually with a trial and error approach, based on detailed description of the CA experiment and expert knowledge. As yield was the only available long-term variable in the CA experiment, the aim for this adjustment were to decrease the difference between simulated and reported yield responses of CA, comparing to the treatment of CTR-CTW, and the difference between simulated and reported yield trends (9 years) for each CA. Parameter descriptions and the calibration rules are listed in Table 2.

The third step was to optimize the rotation management, including cultivar types and combinations associated with sowing and harvesting date and fertilizer application. We repeated the simulation with varying management combinations until the highest mean yield from 2000 to 2019 was obtained. The optimization was conducted for each grid, resulting in heterogeneous parameters and best management that fit the local environment and CA. The first optimization considered crop calendars and cultivars, which was accomplished by repeating the simulation with various combinations of four indicators – sowing date of rice, maturity day of rice, days intervals between rice harvesting and wheat sowing, and maturity day of wheat. For example, for direct-seeding rice, the optimization gradually decreases rice growth duration and the period between rice harvesting and wheat showing, allowing wheat to be planted earlier and grow longer. Information extracted from the farm surveys was used to define the range for each indicator. PHUs were estimated accordingly from the daily weather and the calendars of each crop rotational sequence. The purpose of this optimization was to identify the best maturity duration of crop cultivars and their combination, with corresponding planting and harvesting dates under CA. This optimization was implemented by integrating the EPIC model with a global optimization algorithm - differential evaluation (Aridia et al., 2011). The second optimization considered fertilizer management. Across 7378 farmer-observations, the median fertilizer application rate was 147 kg/ha N, 76 kg/ha P, 52 kg/ha K for rice, and 140 kg/ha N, 110 kg/ha P, 33 kg/ha K for wheat. The present, 30th, 50th, 70th, and 90th percentile of fertilizer application rates were extracted from the farm survey data and tested in the simulations, with different

Table 2
Parameters calibrated and their estimating rules for the CA simulation in SA.

Calibration Stage	Parameters	Name	Values or estimating rules		References
			Default	Calibrated/estimating rules	
1 - Initialization	PHU	Potential heat unit	–	Gridded based, real-time estimated from fixed sowing and harvest date of (SAGA)	Xiong et al. (2014); Balkovic et al. (2014); Wang et al. (2018)
	HI	Harvesting Index	0.45 (winter wheat), 0.20 (rice)	0.2–0.6 (Gridded and crop based)	
	WA	Biomass-Energy Ratio	35 (winter wheat), 25 (rice)	30–45 (Gridded and crop based)	
2 - Calibration for CAs	Parms (4)	Nitrate leaching ration [0.1–1]	0.5	0.1	Le (2017);Le et al. (2018)
	IOX	Oxygen/depth (0) or Kemanian Carbon/clay function (1)	0	1	
	ICF	C factor calculation equation: (0) use RUSLE C factor for all erosion equation; (1) use EPIC C for all equations except Rusle.	0	1	
	IDN	N_2O lost to atmosphere: (1) Armen Kemanian denitrification method; (2) original EPIC denitrification method	1	2	
	EMX	Mixing efficiency	Varying dependent on tillage operations. The calibration was to decrease the difference between simulated and reported yield response of CA comparing to CTR-CTW for current and subsequent crop.		EPIC user's manual version 0810, 2013
	RR	Random surface roughness created by tillage operation			
	TLD	Tillage depth in mm			
	RHT	Ridge height			
	RIN	Ridge interval			
3 – CA optimization	Day of sowing	Day of rice and wheat sowing	Universal value in SA	Varying across grids	
	Day of Harvesting	Day of rice and wheat harvesting	Universal value in SA	Varying across grids	
	Day interval	Days between rice harvesting and wheat sowing	30	10–45, varied depending on location	
	PHU	Potential heat unit	Estimated from weather	Estimated from the new calendar and weather	

application methods (e.g. broadcasting, incorporating) and timing (split into twice or three times). The combination of crop management factors that reached the highest productivity level was subsequently identified for each grid cell and for each of the five CA treatments.

3. Results

3.1. The setup of the regional simulations

The baseline simulation appropriately captured the spatial pattern of reported yields. For both rice and wheat, over half of the grids exhibited minor differences (less than 5%) between the simulated (mean for

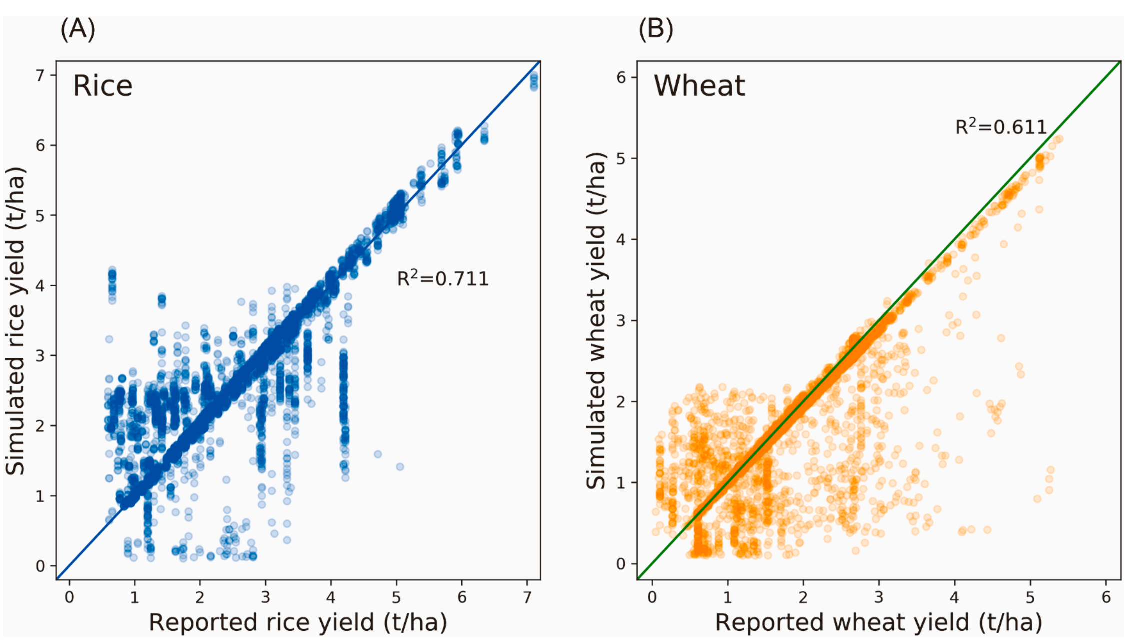

Fig. 3. Comparison between reported and simulated yields. a) rice, b) wheat. Reported yield was obtained from SPAM, for the year around 2000, while simulated yield was mean over 1996 – 2005.

1996–2005) and reported yields according to the SPAM database, with an R^2 of 0.71 and 0.61 respectively (Fig. 3). Similarly, the simulations produced the highest yield for rice in the IGP region and southern India, and the highest wheat yield in western IGP (Fig. 4). These location specific high yields mimic the actual yield patterns in SA, given the western IGP's comparatively favorable climate, assured irrigation availability, larger fertilizer inputs, and earlier sowing of wheat after rice as compared to the eastern IGP. While moving to the east, simulated yields were either limited by maximum temperatures or low input applications, resulting in a relatively lower yield, particularly for wheat. For some grids, the model failed to generate economic yields, such as rice in Bangladesh and parts of Pakistan. This was because of the complexity of the crop calendar in these regions and the challenges associated with accommodating multiple crops. For example, there are three partially overlapping rice seasons (monsoon season 'aman' rice, winter 'boro' rice, and spring 'aus' rice) in Bangladesh. We chose the 'boro' season in the simulations as it fits well in the rice-wheat rotation, but this configuration tended to produce a low rice yield compared to the simulations with the other two rice seasons. In addition, low fertilizer input was another factor limiting the yields in some areas, particularly in Pakistan.

3.2. Simulated yield response of CA in the long-term trial

The yield response of the six treatments compared in the long-term experiment was simulated by the EPIC model with gridded weather and soil inputs and actual tillage operation (Table 1). In all cases, simulated mean yields were not significantly different from observed values ($p > 0.05$) for rice, wheat, and the RW system (Fig. 5). Simulated yield trends were similar to the observations for most cases except wheat under the ZTDSR-ZTW+R and PBDSR-PBW+R treatments. All five CA configurations exhibited yield benefits (average over nine years) compared to the control, with the highest yield gain under ZTDSR-ZTW+R and the lowest under CTR-ZTW (Fig. 6). Wheat yield exhibited small to substantial increases for all the five CA treatments, while rice yield decreased under three CA treatments, i.e., ZTDSR-CTW, ZTDSR-ZTW, and PBDSR-PBW+R. Although yield pattern was similar between the simulations and the experiment, yield variability in the simulations

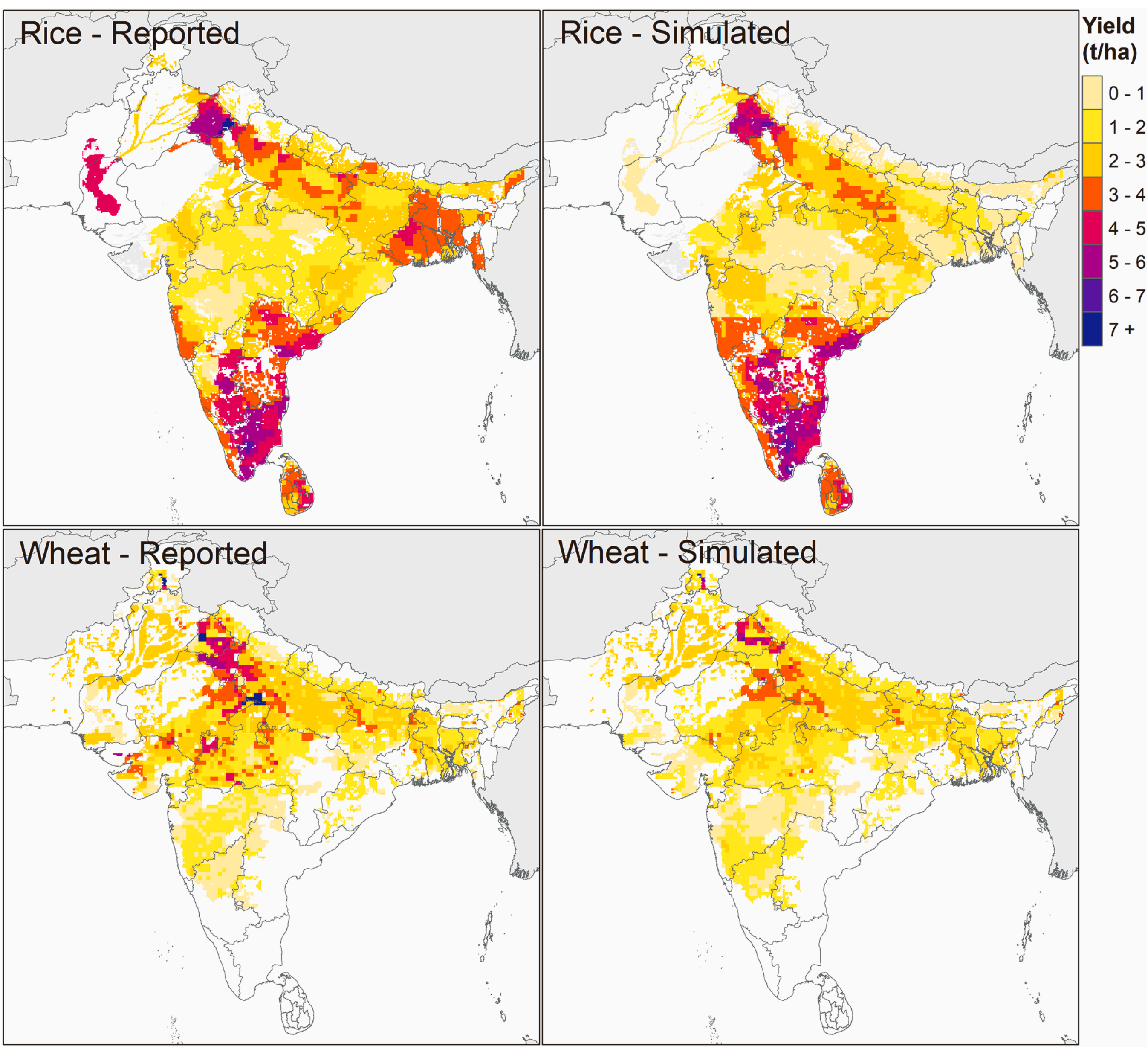

Fig. 4. Comparison of spatial pattern between reported and simulated yield. The white color indicates no rice/wheat coverage data.

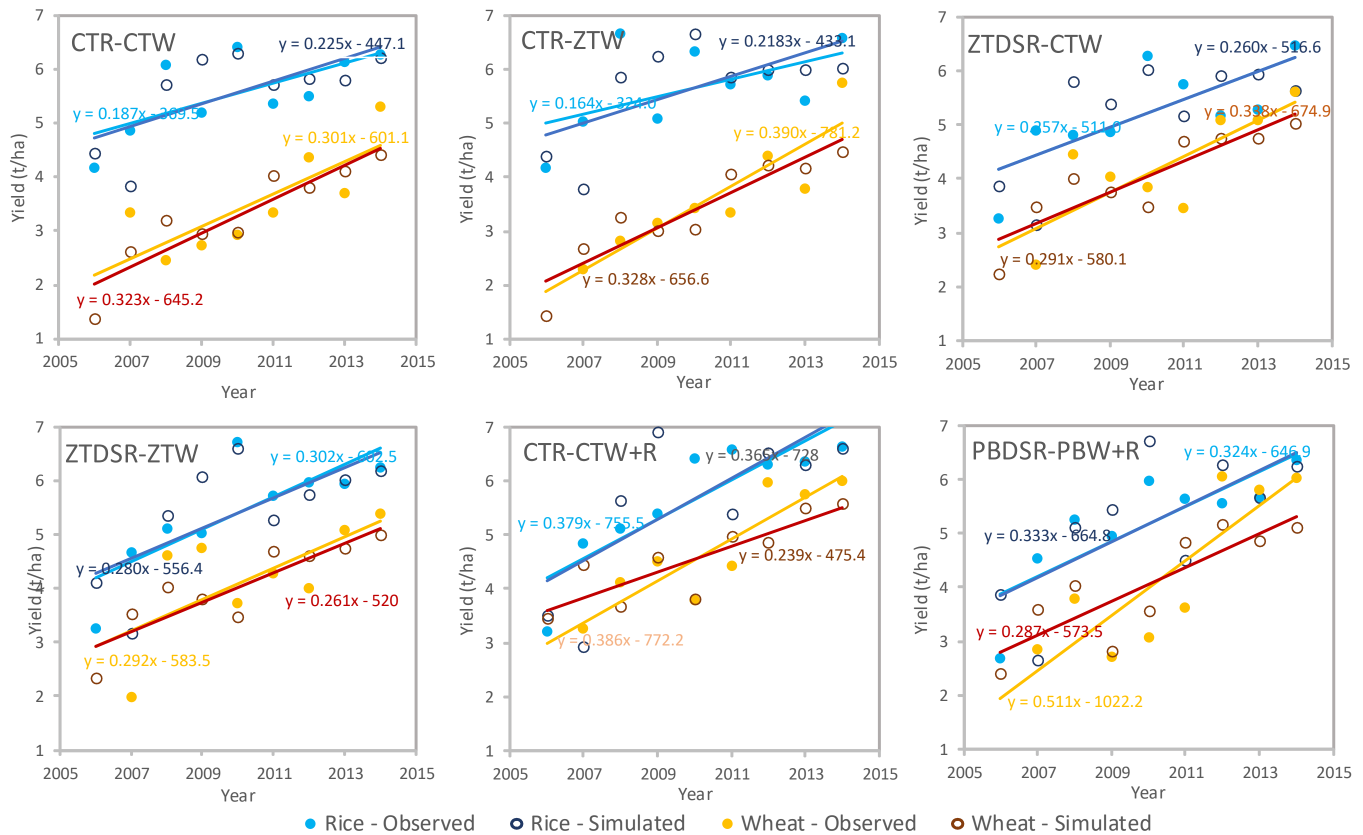

Fig. 5. Simulated and observed yields and trends for six tillage and establishment treatments in long-term CA experiment in Samastipur, Bihar, India. CTR–CTW: conventional till puddled transplanted rice followed by conventional tilled wheat; CTR–ZTW: CTR followed by zero tilled wheat; ZTDSR–CTW: zero-till direct seeded rice followed by CTW; ZTDSR–ZTW: ZTDSR followed by ZTW without residues; ZTDSR–ZTW+ R: ZTDSR followed by ZTW with residues; and PBDSR–PBW+ R: direct seeded rice followed by wheat both on permanent raised beds.

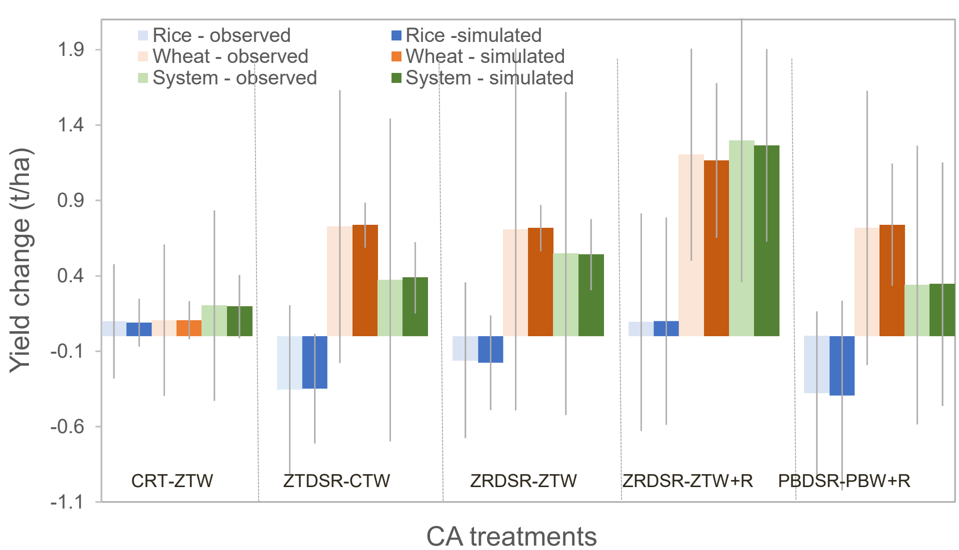

Fig. 6. Simulated and observed yield difference of the five CA treatments (average over nine years) in long-term experiment, compared to the control (CTR-CTW). The vertical line in each bar denotes the standard deviation of the years. CTR–CTW: conventional till puddled transplanted rice followed by conventional tilled wheat; CTR–ZTW: CTR followed by zero tilled wheat; ZTDSR–CTW: zero-till direct seeded rice followed by CTW; ZTDSR–ZTW: ZTDSR followed by ZTW without residues; ZTDSR–ZTW+ R: ZTDSR followed by ZTW with residues; and PBDSR–PBW+ R: direct seeded rice followed by wheat both on permanent raised beds.

was generally smaller than field observations under the experiments, indicated by a smaller standard deviation in all cases.

There are no spatially explicit and widely distributed reported area and yield data for the rice-wheat rotation in SA. We therefore conducted a baseline RW simulation in grid cells with the same inputs and parameters as those described in Section 3.1. The simulation applied current tillage practices represented by CTR-CTW (Table 1), and considered the nutrient carryover effects of the crop rotation. The reported gridded fertilizer and a fixed crop calendar (the middle points of reported sowing and harvesting windows) were used as the driver. Fig. 7 indicates simulated yield patterns of the RW system. Mean productivity was 5.9 t/ha for the RW system, with 3.7 t/ha for rice and 2.2 t/ha for wheat. RW system yields ranged from 4 t/ha to 14 t/ha. Yield was higher in western IGP than in eastern IGP, with the highest simulated yields observed in Punjab. For most areas, particularly those with higher productivity, rice dominated the system with a much higher yield. However, wheat grown

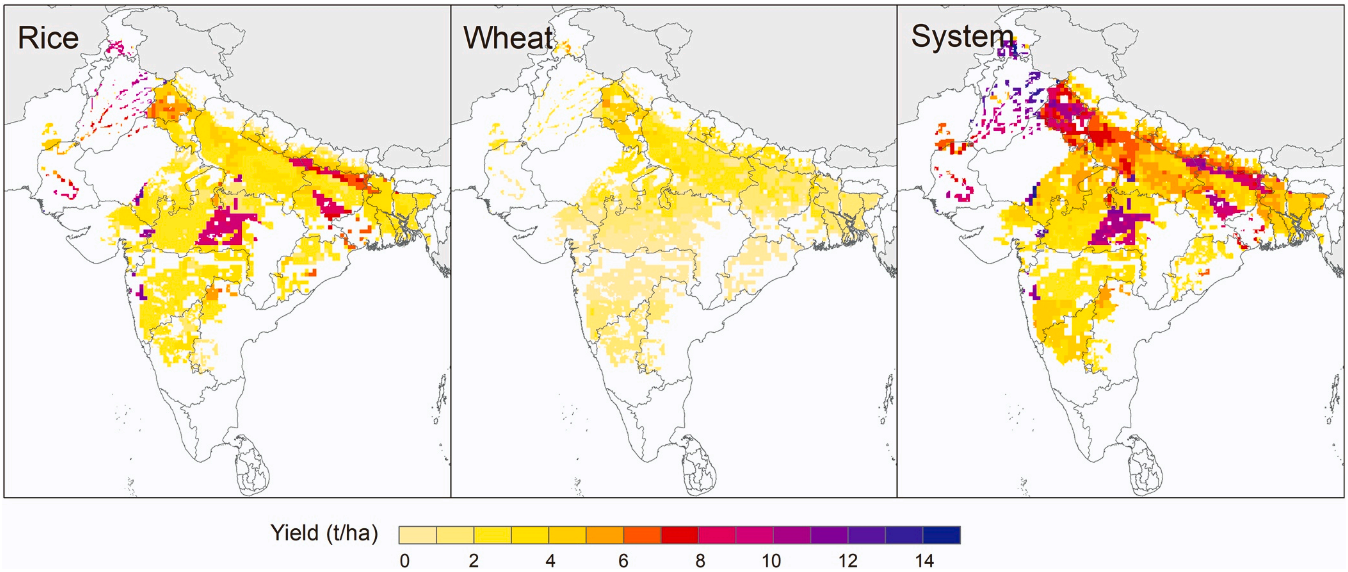

Fig. 7. Yields of rice, wheat, and RW system in baseline simulation.

in the winter generally produced a relatively low yield of around 2 t/ha, partly because of the adverse effects of rice's wet-tillage practices on soil physical properties and delay in wheat sowing caused by late harvesting of rice and the time taken for land preparation prior to sowing under conventional tillage practices.

Yield changes for each of the five configurations of either partial or complete CA practices but keeping current rotation management are shown in Fig. 8. In contrast to the experiment, all configurations of CA practices resulted in adverse effects on crop yields in simulations, although large spatial variabilities existed ranging from negative to positive. The mean yield response for the system spanned from –4.9% under the partial implementation of CA with CTR-ZTW to –18.1% under the full implementation of CA with ZTDSR-ZTW+R. This yield penalty is larger for wheat than for rice in these partial CA practices.

3.3. Optimization of crop phenology

Optimization of RW rotation through modifications in crop maturity duration and corresponding sowing and harvesting date substantially increased wheat yield, resulting in a mean increase of 16% for the RW system in the simulation under CTR-CTW. Rice and wheat responded differently to optimization, with 7.1% and 36.0% increases in simulated yield for each crops, respectively, across all RW grid cells over non-optimized crop calendar (Fig. 9). Simulated yield response of the different configurations of CA and sowing and maturity duration at more optimal calendar dates improved phenology and presented contrasting results from the baseline simulation with initial parameters, and with similar patterns as in the CA experiment. The mean productivity of the RW system under all the five CA configurations all showed significant increases ($p < 0.05$), ranging from 4.2% (CTR-ZTW) to 8.3% (ZTDSR-ZTW+R) (Fig. 10). Yield increase was more substantial for wheat under treatments with dry seeding of rice because of the decreased rice duration. For example, the mean yield of wheat increased by 38.7% under the partial CA treatment ZTDSR-CTW. However, rice yield decreased under CA, with a mean decrease of 2.1% across the five configurations of CA practices.

As expected, simulated yield of the RW system with optimized establishment and maturity duration positively affected interactions

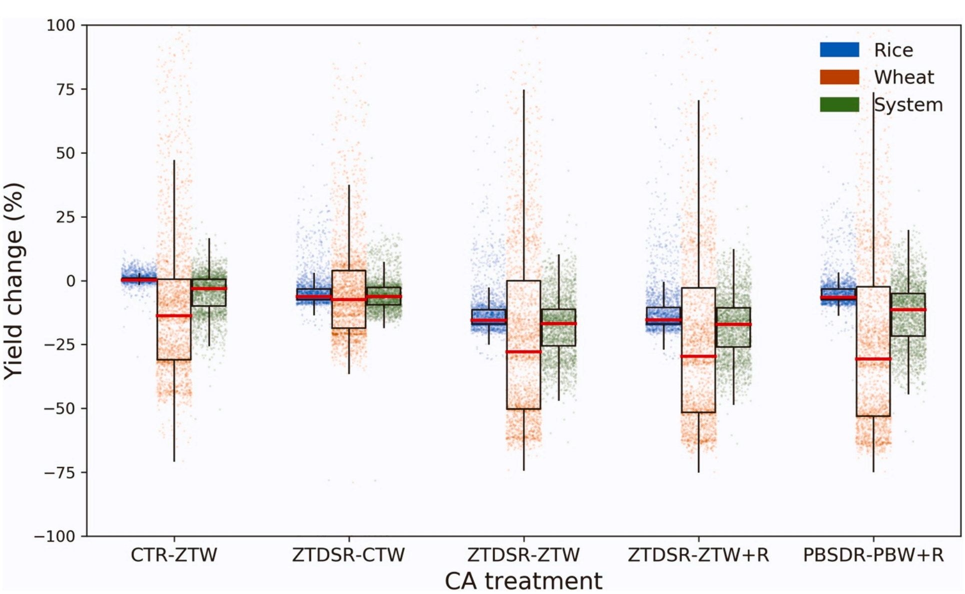

Fig. 8. Simulated yield response of the five CA treatments with initial calendar and model parameters across all RW grids. Yield change is the relative change (%) compared to the CTR-CTW. Boxes indicate the interquartile ranges (25–75%) of the data, red lines the medians, and whiskers the highest and lowest values of yield change. CTR–CTW: conventional till puddled transplanted rice followed by conventional tilled wheat; CTR–ZTW: CTR followed by zero tilled wheat; ZTDSR–CTW: zero-till direct seeded rice followed by CTW; ZTDSR–ZTW: ZTDSR followed by ZTW without residues; ZTDSR–ZTW+ R: ZTDSR followed by ZTW with residues; and PBDSR–PBW+ R: direct seeded rice followed by wheat both on permanent raised beds.

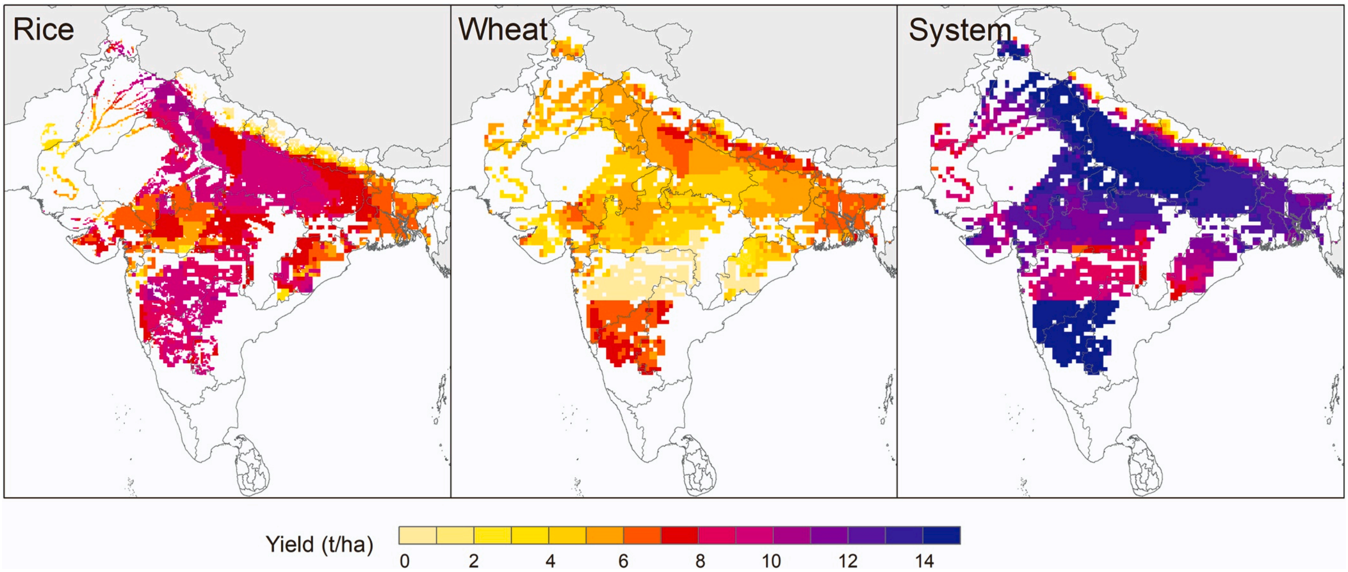

Fig. 9. Simulated rice-wheat rotation yield with the optimized crop phenology and calendar.

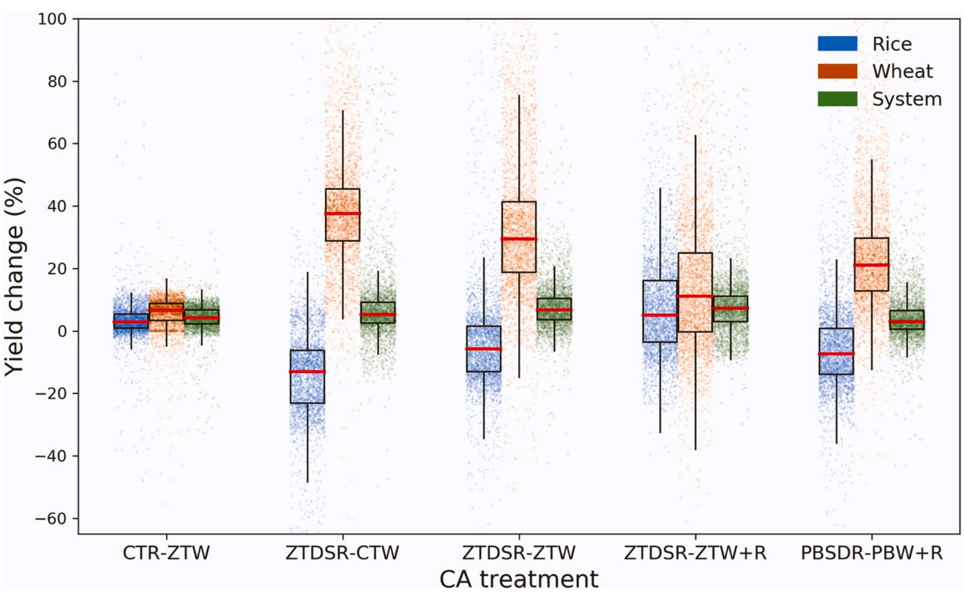

Fig. 10. Simulated yield response of the five CA treatments with current calendar across all RW grids. CTR–CTW: conventional till puddled transplanted rice followed by conventional tilled wheat; CTR–ZTW: CTR followed by zero tilled wheat; ZTDSR–CTW: zero-till direct seeded rice followed by CTW; ZTDSR–ZTW: ZTDSR followed by ZTW without residues; ZTDSR–ZTW+ R: ZTDSR followed by ZTW with residues; and PBDSR–PBW+ R: direct seeded rice followed by wheat both on permanent raised beds.

between climate and phenology, resulting in highest yield in western IGP, with a mean productivity approaching to 14 t/ha. Yield in central India was also high because of the relatively cooler climate for wheat under higher elevation (Fig. 11). Yield response under the different CA treatments had different spatial patterns, and also between crops within each configuration (Fig. 11). For example, CA treatments tended to decrease rice yield in most areas, with the largest yield loss under the CA with zero-till for both crops, such as ZTDSR-ZTW. In contrast, wheat yield tended to increase in most locations with the implementation of different CA configurations, with the largest increase under the partial CA rotation of ZTDSR-CTW in the IGP. When management was optimized, however, RW system productivity exhibited small to moderate growth in most areas under all configurations of CA, especially in the IGP.

3.4. Optimization of fertilizer application

According to the farm survey, the 90th percentile of fertilizer doses was 220 kg/ha N, 162 kg/ha P, 99 kg/ha K for rice, and 201 kg/ha N, 177 kg/ha P, 93 kg/ha K for wheat. We assumed them as the maximum application rate for the system. We operated the simulations with five fertilizer application scenarios (present, 30th, 50th, 70th, and 90th percentile of the fertilizer application rates across the farms). Application time was optimized according to crop requirements by splitting into several times.

Yields under the five CA treatments and five fertilizer application scenarios across all RW grids in SA were aggregated into regional mean yield, with potential RW areas as the weight factors (Fig. 12). Our results suggest that RW productivity in SA can be increased by applying more fertilizer, with the highest increase of 43.2% under the maximum fertilizer application scenario over CTR-CTW. However, the difference in yield benefit due to heightened fertilizer rates and between the 70th and the 90th percentile fertilizer rates appears to be small (less than 2%), suggesting a decrease in fertilizer recovery efficiency above 70th percentile of the dose described above. Considering the five CA treatments, CTR-ZTW exhibited the largest yield benefit (+4.9%) averaged

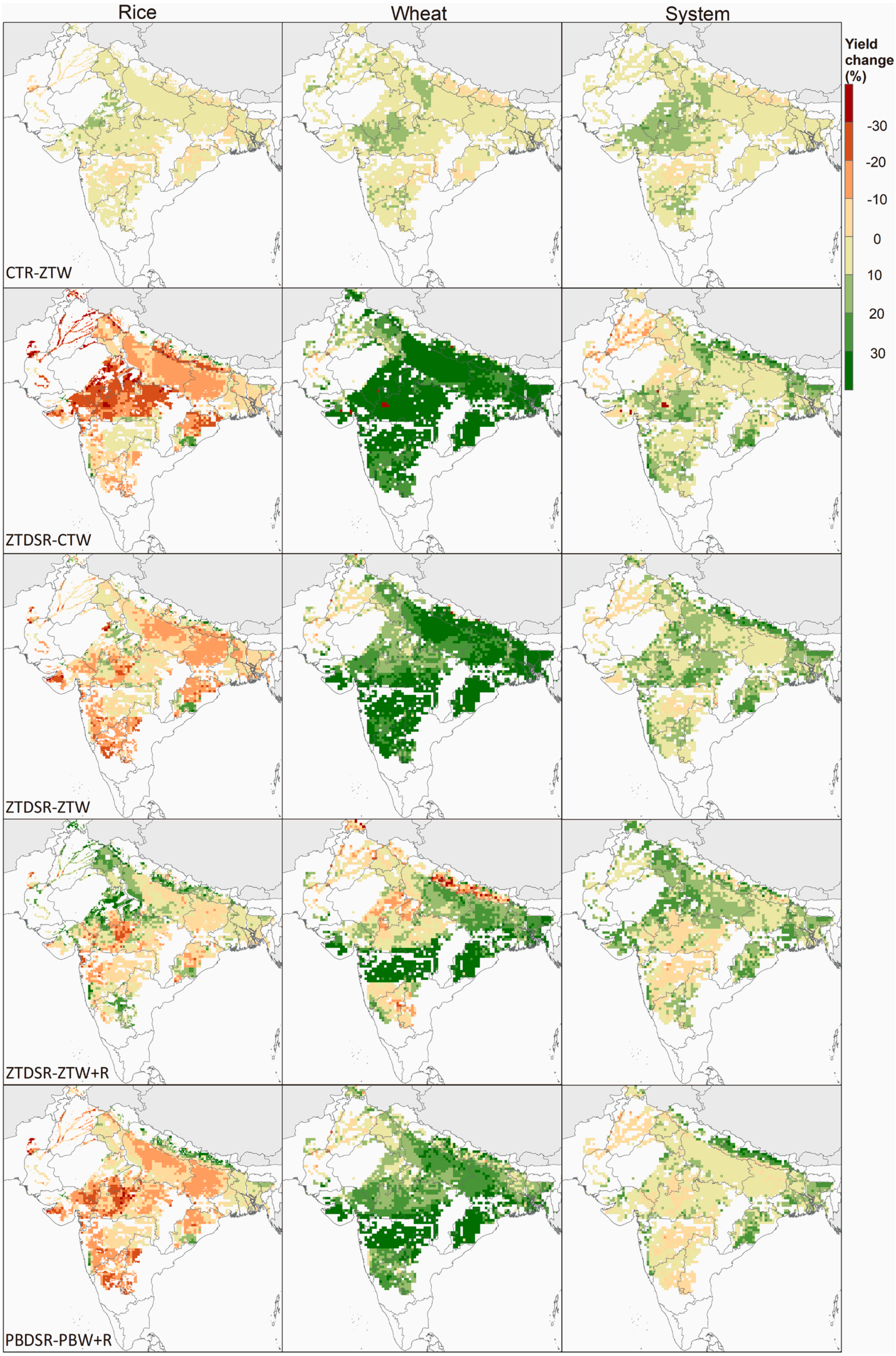

Fig. 11. Simulated yield response of five CA treatments Yield response is the percent compared to the simulated mean yield under CTR-CTW. CTR–CTW: conventional till puddled transplanted rice followed by conventional tilled wheat; CTR–ZTW: CTR followed by zero tilled wheat; ZTDSR–CTW: zero-till direct seeded rice followed by CTW; ZTDSR–ZTW: ZTDSR followed by ZTW without residues; ZTDSR–ZTW+ R: ZTDSR followed by ZTW with residues; and PBDSR–PBW+ R: direct seeded rice followed by wheat both on permanent raised beds.

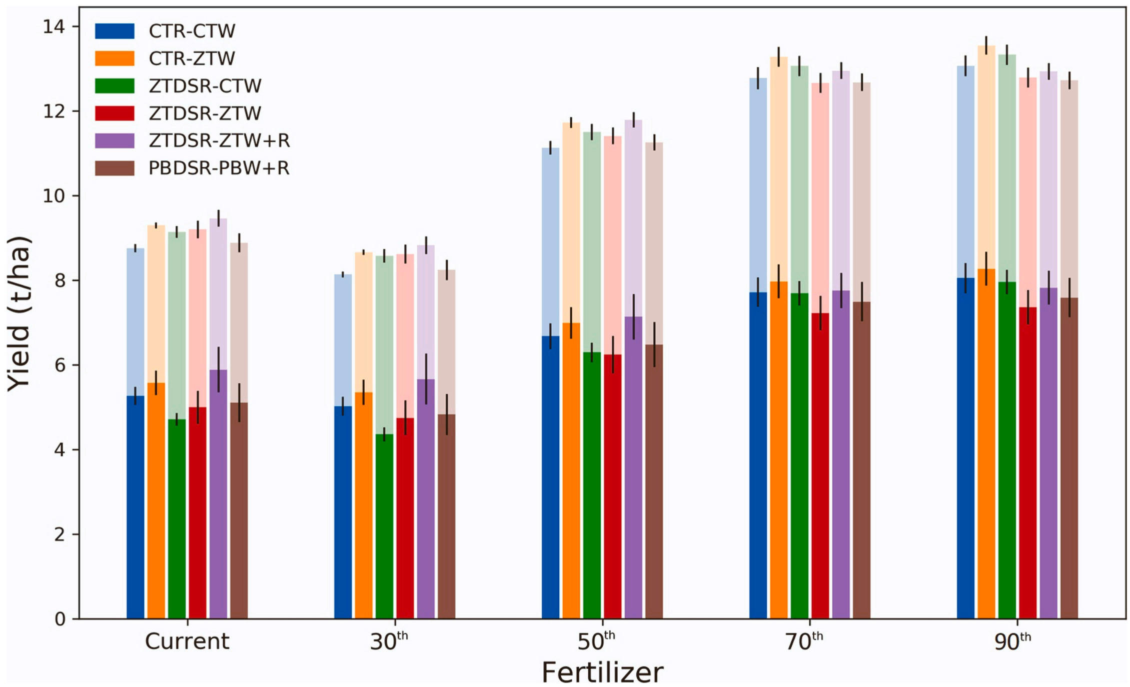

Fig. 12. Yield response of the six treatments to fertilizer application amount. Max indicates the 90th percentile application amount estimated from the crop cut/ survey. 30th, 50th, 70th, denote reduced fertilizer application scenarios, and the current means the actual application amount for wheat and rice in each grid reported by Muller et al. (2012). The light-colored legend (top) shows wheat yield, and the dark-colored legend (bottom) shows rice yield. Total length of the bar represents system yield. CTR–CTW: conventional till puddled transplanted rice followed by conventional tilled wheat; CTR–ZTW: CTR followed by zero tilled wheat; ZTDSR–CTW: zero-till direct seeded rice followed by CTW; ZTDSR–ZTW: ZTDSR followed by ZTW without residues; ZTDSR–ZTW+ R: ZTDSR followed by ZTW with residues; and PBDSR–PBW+ R: direct seeded rice followed by wheat both on permanent raised beds.

across the four fertilizer scenarios, while PBDSR-PBW+R showed a small yield penalty (−0.2%).

4. Discussions

4.1. Modeling the spatial heterogeneity of CA performance

Process-based models have been increasingly used to investigate the consequences of CA, but the majority of studies are limited to a few experimental sites where management practices and detailed outcomes (e.g. yield, biomass, soil organic carbon) were observed (Devkota et al., 2015; Ngwira et al., 2014). Modeling studies considering the application at large spatial scales are however very scarce, even though gridded modeling techniques have substantially advanced (Folberth et al., 2019; Muller et al., 2017; Rosenzweig et al., 2014). The lack of effort to apply spatially gridded simulation to CA may be due to several factors. First among these are the limitations of most modeling frameworks to accurately represent the complexity of CA. CA is a general term for a series of resource-conserving agricultural practices, like practicing reduced tillage, crop rotation, and the maintenance of soil cover through living or dead mulches (Kassam et al., 2011). In practice, CA is widely adapted as an alternative planting and tillage technique with minimum or zero tillage combined with crop residue retention and crop rotation as fundamental components. This results in complicated crop-soil-management interactions. Many of these interacting factors are not sufficiently accounted for in crop simulation models and are represented in the model with limited way (Kollas et al., 2015). For example, the CA practices of permanent raised-beds have been widely studied in the RW systems of SA (Singh et al., 2009). The associated temporal change of soil bulk density and water infiltration capacity due to tillage and soil cover are poorly represented in models at this time. Second, lack of calibration and parameterization of models in long term CA experiments involves many temporal changes in soil properties. Although long-term experiments exist and have facilitated modeling through model calibration and evaluation, accurate simulation at the spatially diverse regional level requires experiments at multiple sites with coordinated data collection for variables of key interest. Such networks are however currently not widely available.

With the example of CA in SA's RW system, our results suggest the feasibility of the CA simulations using a gridded crop simulation model. Based on learnings from our study, three steps appear to be indispensable to achieve robust regional modeling of CA. These are (1) long-term CA experiments to adjust the model parameters relevant to tillage, (2) a regional scale dataset for calibration of the cropping system of interest, and (3) sufficient farm survey data to represent the diversity of practices across farms. Mean yields and yearly trends of the different configurations of partial or complete CA in our study were largely captured by the model, suggesting that seasonable representation of nutrient carry-over and the effects caused by tillage could be appropriately represented. There was a slight underestimation, however, in the yield slope for wheat under treatment in which residue was maintained as mulch, i.e. under PBDSR-PBW+R, likely because of the limited representation of mineralization pattern of surface retained residues, nutrient absorption and extent of transfer of nutrients from crop residues to soil nutrient pools over the season and long run in the model. Over long run, the retention of residues on the soil surface can increase soil organic carbon content (SOC) and improve the soil physical and functional properties, such as reduction in bulk density, increase in water holding capacity and hydraulic conductivity (Parihar et al., 2016). These effects, however, may be counteracted in the short term through nitrogen immobilization and waterlogging events during heavy rainfall or intensive irrigation (Turmel et al., 2014). Many of these variables can be parameterized in modeling frameworks, but the temporal changes caused by long-term covering need specific routines applicable to CA practices that remain understudied.

Besides the calibration of CA practices themselves, regional calibration for the RW system is important for the robust evaluation of different CA configurations. This is evidenced by the contrasting results between the baseline simulation and the simulation with management optimization. Although the baseline simulation with conventional gridded modeling approach reproduced the pattern of reported yields for rice and wheat, single crop simulations need to be adjusted/optimized to account for the interacting factors like crops, timings, soil, weather etc. For example, wheat yield in the baseline simulation was much lower than the simulation with optimized sowing/harvesting dates and phenology. Yield response of CA was more negative in the baseline simulation than the simulation with optimization. This is because calibration in conventional gridded models mostly focuses on a single crop (Xiong et al., 2014, Folberth et al., 2019). Such studies parameterized the model to represent regional yield patterns with specified dates for crop establishment and harvest, and consequent phenology as the restricting factor, regardless of the specific requirements inherent to rotational cropping systems. In contrast, model optimization in this study increased the spatial heterogeneity in management (i.e., cultivar growth duration, calendar), allowing the system to accommodate the localized and complicated factors. Examples of complicating factors that must be accounted for in gridded crop rotational modeling efforts include earlier planting of the first crop, and the short window between the harvesting of first crop and the planting of the subsequent crop in addition to biophysical limitations including soil types and drainage classes that are not widely accounted for in most studies. Importantly, because of the coarseness of most gridded datasets, including the calendar of crop operations in this study, we employed large scale farm survey across India, Nepal and Bangladesh to supplement gridded data. This helped to facilitate more appropriate calibration and as such substantially increased our ability to more accurately account for and simulate the extreme heterogeneity in management practices as they are applied by farmers themselves.

4.2. Heterogeneity of yield responses under CA configurations

In agreement with the findings from experimental studies and meta-analyses, simulated yield responses in the current study varied widely depending on the crop, region, and management interactions. Our simulations that aimed to optimize management shows that yields for wheat were benefited under CA, with an increase of 8.9% averaged across the five CA configurations studied. Observed yield exhibited an increasing trend for all six treatments because of nutrient accumulation over seasons and due to adoption of long duration variety in the third year of the experiment (Jat et al., 2014). Similar findings have been reported in many studies that showed higher wheat yield was achieved under CA in the RW system, particularly when combined with residue intention (Sharma et al., 2018; Samal et al., 2017; Gathala et al., 2011). Partial configuration of CA with no-tillage applied to only one of the crops in rotation experienced higher yield gains from fertilizer increase. For example, CTR-ZTW, ZTDSR-CTW both exhibited larger yield benefits with higher fertilizer application scenarios. This suggests decline in soil's nutrient supplying capacity in systems where conventional tillage is practiced in between the zero tillage events in RW rotations, for which loss of nutrient could be a case. In some long-term experiments in SA, it has also been observed that averaged wheat yields under no-till with or without residue retention relative to conventional tillage tended to be higher (Singh et al., 2020). Yield gains with no-till for wheat were largely due to the time saved in land preparation that enabled earlier planting of wheat that permits the crop to escape from disruptions to flowering, pollination, and grain filling (Krupnik et al., 2015; Gupta and Seth, 2007).

A surprising finding from our results, however, was the large negative effects observed for wheat in the baseline simulation, contradicting the results from the optimization simulations and also the experiments. This was likely caused by suboptimal planting and harvesting times extracted from the SAGE calendar dataset, and specifically by the extremely late sowing dates for wheat into later December in much of the eastern IGP, and with pockets of potentially unrealistically late December sowing also represented in India's Haryana and Punjab states (Sacks et al., 2010). The SAGE data have however been used widely for global gridded simulations and was developed from sub-national statistics and existing observations of crop planting and harvesting dates for specific crops, although observations indicate that refinement for wheat sowing dates in SA might be in order. Using the middle date of the sowing and harvest ranges might result in a simulation that would not in reality permit appropriate RW rotation as it is practiced in CA, such as later or earlier sowing, simulation of crop or cultivar with excessively long or short growing duration, or an insufficient or long turn-around period between rice and wheat. These observations suggest the importance of refining the SAGE dataset and/or developing additional gridded products to represent rotational system crop calendar with much more explicit calibration to represent the farmers' practices and local environments.

In contrast to wheat, rice yield was negatively affected in SA under most of the CA configurations, particularly those in which residues were exported from the system rather than used as mulch. Rice in SA is typically grown under puddled soil conditions, which typically entails intensive tillage operations to help maintain flooded conditions during the growing season. Puddling has benefits on rice through better weed control, reduced percolation loss of water and nutrient, quick establishment of seedling and improvement in nutrient availability due to reduced conditions (Gathala et al., 2011). Evidence that no-till and conversion from puddling to dry seeding in rice systems entails large shift in management and can lead to yield declines has been frequently reported (Su et al., 2021; Singh et al., 2020; Sharma et al., 2018). However, our data indicate that residue retention can partly offset this decline due to the maintenance of soil moisture and increase of nutrient availability.

Regarding spatial heterogeneity in yield response of CA, we simulated increased system productivity in the eastern IGP while a small decrease or neutral change in western IGP. As most of SA's RW area is located in the IGP, we further investigated the response variation across grids in this region (Fig. 13). Similar to the values from experimental observations through experiments reported in meta-analysis (Jat et al., 2020), simulated yield, and especially wheat yield, exhibited relatively larger gains in eastern IGP than in western IGP. For most of the CA treatments studied, simulated yield responses were close to the mean of responses estimated from the 136 CA experiments identified but exhibited a much smaller range than the observations. This suggests that models can not only be used as an auxiliary tool to reduce the time and expenditure required by the CA experiments; they can also decrease some of the uncertainty associated with evaluating the adaptation of CA practices in different locations. That said, long-term experiments lying distributed across environmental gradients between and within regions hold good for modeling various 'calibrations'.

4.3. Limitations of this study

We recognize this study has several limitations. First, we calibrated the model only for yield and did not account for the fact that CA is often adopted by farmers for its cost-saving qualities accrued from reduced fuel and labor use (Jat et al., 2014). CA can also have important environmental advantages not considered in the current study, although future modeling efforts should seek to examine the multi-criteria performance of CA. For example, dry direct seeding of rice under CA can reduce methane emissions and hence limit contributions to greenhouse gas by eliminating prolonged soil anaerobic conditions during land preparation (Kumara et al., 2020). In addition, rice residue retention through no-till practices for wheat planting eliminates the need to burn residues to clear fields for tillage, contributing to the improvement of air quality in SA (Shyamsundar et al., 2019). As the EPIC was designed to evaluate crop-environment interactions, especially the effects on soils and emissions (Izaurralde et al., 2006), these environmental and economic consequences should be included in further studies and evaluated

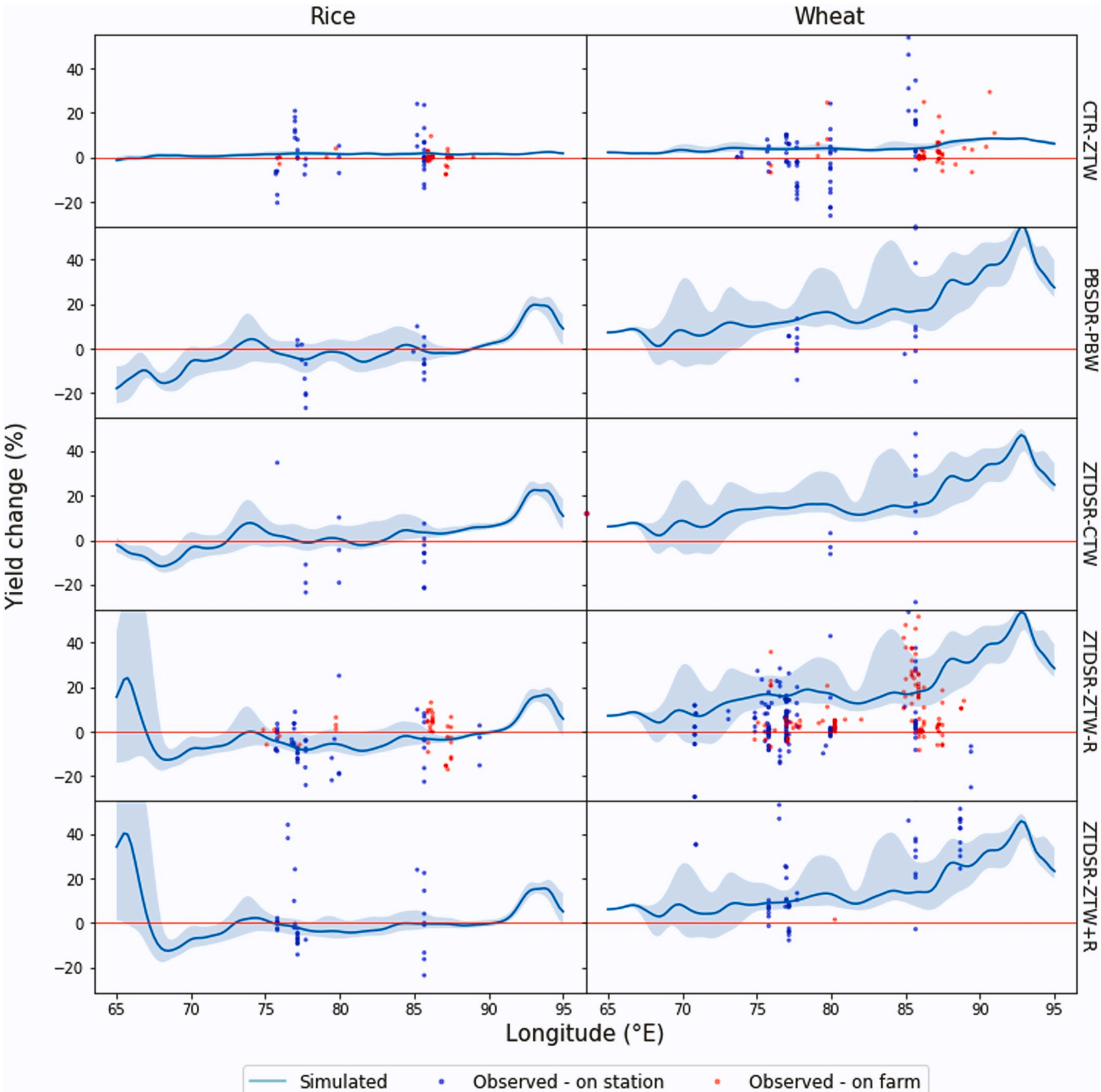

Fig. 13. Simulated yield responses of the CA in the IGP under no nutrient limitation, compared with observed yield responses of corresponding CA from the meta-study of Jat et al. (2020).

for trade-offs and synergies among configurations of CA using available observations of interests from long-term experiments.

Secondly, our simulations could still benefit from improvement to increase the representation of important biophysical procedures relevant to CA. For example, in the site calibration for the five configurations of CA, the lack of temporal effects of CA, especially those related to residue retention and changes in soil physical (e.g., soil structure, bulk density), chemical (e.g., Soil pH., soil organic matter, and nutrient cycling), and biological (e.g., weed suppression, changes in soil microbiology, risks of disease propagation) properties could potentially explain to some extent the underestimation of crop's yield and growth CA observed in this study. EPIC's weakness is also obvious for simulating specific CA practices, such as permanent raised beds. Improvements however can only be made with the help of long-term controlled experiments and increased understanding of the interactions between crops, soil, water, and the atmosphere.

5. Conclusions

While CA has been promoted by international agricultural organizations (such as the United Nations Food and Agriculture Organization) as a promising practice to increase food production and reduce the negative effects of cropping on environment, experimental observations of yield penalties have been commonly observed alongside those reporting positive results. With the SA's RW system, we evaluated yield response from different configurations of partial and full CA practices on the performance of RW system yields across SA. After the calibration of the process-based model with long-term experiment and geospatial data, we applied a large scale dataset from farm surveys and meta-analysis of experiments to fine-tune models and optimize management practices, particularly those pertaining to crop establishment and harvesting dates, in addition to nutrient management. The resulting regional simulations were used to investigate the yield outcomes of five configurations of partial or full implementations of the CA principles of no tillage, rotation, and soil coverage through residue retention across environments. By testing these configurations in SA's predominant RW rotational areas, we confirm that there is the potential for yield gains under the region's RW system – particularly when measured as the sum of yield for both crops. However, this potential can only be achieved by modifying other system-level management factors, treating CA as a location-specific management approach in which fertilizer rate and placement, planting and harvesting dates, and cultivar duration need to be carefully optimized. There is also the potential of simulating the reduced requirements for fertilizers in the future years, on account of increased organic carbon with the successive retention of residues. Thus, reducing the harmful environmental effects of over-fertilization, caused by leaching, volatilization and runoff. While promising, these results must also be balanced with appropriate studies of environmental outcomes and the socioeconomic and cultural factors that may permit or limit farmers' ability to implement optimal management in practices; with lessons from such studies used to balance agronomic and modeling studies for real-world feasibility to inform agricultural development and policy efforts.

CRediT authorship contribution statement

Wei Xiong and Tek B. Sapkota conceived the study. Tianning Zhang, M.L. Jat, Raj Kumar Jat, Saral Karki, Harisankar Nayak, Asif Al Faisal, and H.S. Jat collected and processed the data. Tianning Zhang and Wei Xiong conducted the simulations, Tianning Zhang, Wei Xiong and Tek B. Sapkota analyze the results and wrote the paper, M.L. Jat, Carlos Montes, Timothy J. Krupnik, Harisankar Nayaki, and BG contributed to the writing. All authors read and agreed on paper.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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